Rich and Unhappy: A Quantitative Analysis of Internal Trade and Migration in China

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Abstract

We quantitatively evaluate the income and welfare impacts of inter-city migrations in China. We develop a multi-city, multi-sector model with heterogeneous firms and imperfect labor mobility, in which the city and firm size distributions, together with trade and migration patterns are all determined endogenously in the general equilibrium. We implement this model to 279 Chinese prefecture level cities, and estimate the bilateral trade and migration costs using real world geography of transportation networks. We find that inter-city migration alone between 2000 and 2005 is able to explain 41 percent of the change in real income in the data. However, about 3/4 of the gain in real income are offset by the higher congestion costs in large cities. Native population in large cities bear most of the cost, while all the welfare gains are collected by the migrants. 80 percent of the cities, including Beijing, suffer welfare loss due to migration. Those who are able to gain from migration are the cities either located closer to the megacities or at the nexus of transportation networks.

Keywords: regional trade; migration; welfare; economic geography

JEL Classification: F1; F4; R1; O4

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1 Introduction

Over the past couple of decades, China has witnessed the largest wave of population migration in the human history. After the easing of restrictions on household registrations (Hukou) in post-Mao era, an estimated 340 millions of individuals (Chan [2011]) — roughly the entire population of the U.S. — have trekked thousands of miles away from their hometown, searching for better working opportunities, and potentially a new life. Undoubtedly, migrations at such scale have altered the economic life of every Chinese citizen, migrants or not, along many dimensions. Inflows of migrants bring in fresh entrepreneurial ideas, ample labor supply and consumption demand to the destination cities. However, at the same time, they also compete with the natives for the scarce resources, and worsen the already mounting problems of congestion, pollution, and high housing prices in the large cities. The controversial nature of migration problem calls for comprehensive and quantitative assessments on the income and welfare changes in each city due to migration. This paper attempts to offer some first answers to these important questions.

We develop a multi-city multi-sector quantitative framework with labor mobility to study the impacts of internal migration. Our framework is based on the trade models with heterogeneous firms, following the ideas of Melitz [2003], Eaton et al. [2011], and Di Giovanni and Levchenko [2012]. We extend this line of models with endogenous migration decisions. Individuals choose their preferred cities depending on the relative real income and congestion dis-utility, geographic distance from hometown, and idiosyncratic preferences. The city and firm size distributions, trade and migration patterns, along with product and factor prices are all determined endogenously in the general equilibrium — this enables us to perform a series of rich quantitative studies.

We implement our model to the 279 prefecture-level Chinese cities. We calibrate the structural parameters to match the moments in input-output linkages, firm size distributions, internal trade patterns, and magnitude of migration in the data. Our benchmark calibration successfully captures the key untargeted moments, such as bilateral migration flows, city size distributions, and wage distributions across cities.

The geographical locations of cities, together with their relative positions in the traffic

networks arguably play important roles in determining both the bilateral trade and migration flows. However, existing literature on internal migrations in China has never taken the geography — the road, railway, and waterway networks — into account. One of our major contribution here is to estimate the between-city trade and migration costs matrix based on the real world geography of China. Our estimation strategy follows the methods outlined in Allen and Arkolakis [2014]. We first digitize a set of highly-detailed maps on Chinese transportation networks with precision at around 1 square kilometers per pixel, and then compute the distance between any two cities conditional on a specific transportation mode using Fast Marching Methods (FMM). Lastly, we discipline the relative weight of different transportation modes by their mode-specific trade volumes in each city, and the overall scale of the matrix by the inter-city-trade/GDP ratio in China. The 279-by-279 iceberg trade costs matrix eventually is able to capture several key moments of internal trade in the data. We believe the trade costs matrix, along with the associated migration costs matrix proposed in this paper can be widely applied to many other China-related studies.

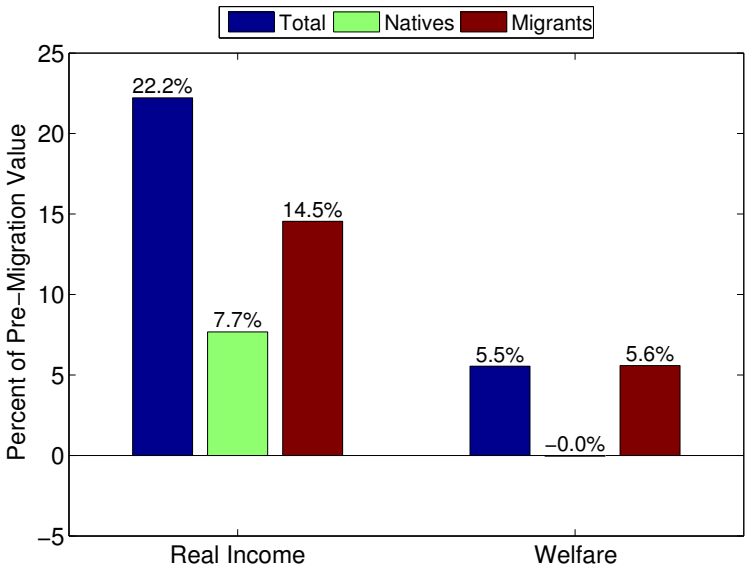


Figure 1: Aggregate Impacts of Migration

Note The graph plots the change in total real income and total welfare between 2000 (pre-migration) and 2005 (post-migration). The values are presented as percentage changes to the pre-migration value. The difference between real income and welfare is the congestion dis-utility.

We find that the inter-city migration between 2000 and 2005 increases the aggregate real income at the national level by 22.2 percent, which is about 41 percent of the real

economic growth in the data. About 65.3 percent of the increase in real wage is the direct result of migration: individuals moving from small and low-income cities into large and rich ones, taking advantage of higher real wage. The rest 34.7 percent of the change is due to the agglomeration effects of migration. In both the data and our benchmark calibration, individuals tend to concentrate in large cities, leading to a more uneven distribution of population across cities. This attracts more firms to enter in the large cities, which in turn offers more varieties to the consumers at lower prices — a key mechanism shared by many models following Krugman [1980]. The productivity gains in large cities also spill over to the other cities through the inter-city trade along the transportation networks, leading to real income gains at the national level.

However, not all the gains in real income can be translated into gains in welfare. The rapidly exploding population in large cities worsens the existing problems of congestion, such as higher housing prices, heavier pollution and traffic jams. Unsurprisingly, these costs are born by the people living in those large cities in China. Once we take the higher costs of congestion into account, we find that the native population — those who choose not to migrate between 2000 and 2005 — are actually slightly worse off. Their gains in real income are completely wiped out by the soaring costs of congestion. At the aggregate level, 75.2 percent of the gain in real income is offset by the change in congestion costs, and welfare only increases by around 5.55 percent between 2000 and 2005. Moreover, as the native population does not gain in welfare at all, all the benefits of migration are collected by the migrants.

The gains in real income are not distributed evenly across different cities. The vast majority of the cities becomes poorer due to migration: out of the 279 cities, only 49 cities enjoyed higher real income. Two main reasons determine the "fate" of cities facing the massive migration. First, all the 31 cities that receive net population inflows fare better in terms of real income — again, the mechanism is the link between city size and number of firms that we have outlined earlier. The relationship between population inflow and real income change is mostly monotonic: income increases faster in cities with larger inflow. Secondly, cities with dwindling population can enjoy higher real wage only if they are located strategically — either close to megacities like Beijing or Shanghai, or at the crossroads between major traffic arteries. The location of these cities made them the most direct

beneficiaries of the productivity booms in the megacities. As a result, they are able to enjoy more varieties of tradable goods at cheaper prices, which offsets the negative implications of emigration, leaving them better off in terms of real income.

Welfare gains are also concentrated into a few cities. Only 55 cities end up with higher welfare, after we take the congestion costs into consideration. Most cities with higher real income will also enjoy higher welfare, however, the relationship between welfare and population inflow is no longer monotonic. The largest city in our sample, Beijing, enjoyed an astonishing surge in real income by 64.2 percent due to a 31 percent net inflow rate. Unfortunately for the natives living there, the inflow of migrants pushed the congestion costs to such high levels that eventually their welfare *drops* by around 0.5 percent. The cities that enjoyed the largest gains in welfare turns out not to be the megacity themselves, but those sit close to the megacities, such as Tianjin, Baoding, and Shijiazhuang, or those located at the nexus of traffic networks, such as Wuhan and Zhengzhou. Those cities are positioned to receive most of the productivity booms in the megacities, and they themselves do not need to bear the high costs of congestion.

Our paper are most closely related to the two papers that focus on the issue of Chinese migration. Tombe et al. [2015] study how misallocation due to goods and labor market frictions affect aggregate productivity in China at the province level. Fan [2015] studies the impacts of international trade on skill premium at prefecture-city level. Our work is different along two dimensions. Both previous papers employ an Eaton-Kortum framework, which is abstract from analysis on firm size distribution and entry dynamics. We show in our work that the linkage between city size, migration, and firm entry is at the core of explaining the changes in real income. Moreover, trade and migration costs estimated in their paper do not take into account the real world geography. We are the first paper to estimate the city-pair level trade costs based on the existing transportation networks. Our results highlight the importance of doing so: geographic locations of cities are central to their gains and loses during the massive migration — and one cannot make such discoveries without incorporating geography seriously into a quantitative framework.

This paper is also related to the growing literature that quantitatively examine the impacts of internal trade costs and migration costs separately or jointly on spatial distribution

of labor and economic activity within countries. Our theoretical framework is an extension of Di Giovanni and Levchenko [2012] and Giovanni et al. [2015], which present a multi-country and multi-sector model with heterogeneous firms and exogenous migration flows following Melitz [2003]. We apply their framework into a multi-city context and extend it by introducing endogenous migration decision at the individual level. Caliendo et al. [2015] also recognizes the role of labor mobility frictions, goods mobility frictions, geographic factors, and input-output linkages in determining equilibrium allocations. They perform a cross-country study and focus on the impact of rise in China's import competition on U.S. regional markets.

Our work is broadly related to the large literature on Chinese economy. Chow [1993] analyzes the path of development of different sectors in the economy. Brandt et al. [2008] further document the process of industrial transformation and the role played by institutions and barriers to factor allocation. Hsieh and Klenow [2009] highlight that the misallocation of capital and output distortions have resulted in sizable loses in China's productivity. Song et al. [2011] argue that the reduction in the distortions associated with state-owned enterprises may be responsible for the rapid economic growth starting in 1992. Our work conveys two important messages. It first highlights the significance of internal migration in economic development. We show that the reallocation of labor alone is able to explain a sizable proportion of real income growth in China, which in turn implies the huge potential of economic growth of further easing the restrictions on labor mobility that still exists as of today. Our analysis on welfare, for the first time, quantifies that around three quarters of economic growth is offset by higher costs of congestion — higher income does not easily translate into higher degree of happiness in the case of China. Our work provides a new insight on the controversy of China to many of its observers: a country that experiences spectacular economic growth is, at the same time, bogged down by brewing social unrest and unhappiness.

The rest of the paper is organized as follows. Section 2 presents the theoretical model. Section 3 describes our calibration strategy and estimation of the trade costs matrix. Section 4 discusses the main results, and section 5 concludes.

2 The Model

We present the theoretical framework in this section. The production side of our model is simply an implication of Di Giovanni and Levchenko [2012], where they develop a multi-country framework. In this paper, we apply them into a multi-city context, and also go beyond by introducing individual migration decision and labor market dynamics.

The economy contains a mass $\bar{L} > 0$ of identical individual workers, and $J > 1$ geographically segmented cities, indexed by $j = 1, 2...J$. There are two production sectors in each city j, namely, tradable and non-tradable sector, denoted as sector N and T, respectively. Individual workers obtain utilities from the consumption of a set of intermediate goods produced in both sectors. Specifically, the utility function of an individual worker in city j takes standard Cobb-Douglas form:

$$U_j = \left[\sum_{k \in \Omega_j^N} y\left(k\right)^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon\alpha}{\varepsilon-1}} \left[\sum_{k \in \Omega_j^T} y\left(k\right)^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon(1-\alpha)}{\varepsilon-1}} - C(L_j), \quad 0 < \alpha < 1$$

where ε represents the elasticity of substitution among all intermediate goods and $y(k)$ is the quantity of intermediate goods k. Ω_j^s denotes the set of available intermediate goods in city j and sector s. α captures the expenditure share on varieties produced in sector N_j. $C(L_j)$ represents the congestion dis-utilities from living in city j. L_j is population size of city j, and $C'() > 0$ so that congestion dis-utility is increasing in population size.

Intermediate goods produced from tradable sector are assumed to be tradable across cities, while intermediate goods from non-tradable sector cannot be traded across cities. This implies that not all the available intermediate goods in tradable sector of city j are produced in city j, but all the available goods in non-tradable sector of city j are produced in city j.

The production of each intermediate good requires input bundles as inputs. To produce an input bundle in turn requires labor, intermediate goods from sector N and T as inputs. The production technology for input bundles also varies between sectors, and this is to capture the idea that the relative contributions of labor and each final good to the production may differ between sectors. Specifically, the production function for input bundle in city j

and sector s takes form:

$$b_j^s = L_j^{\beta_s}\left[\left(\sum_{k\in\Omega_j^N} y\left(k\right)^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon\eta_S}{\varepsilon-1}}\left(\sum_{k\in\Omega_j^N} y\left(k\right)^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon(1-\eta_S)}{\varepsilon-1}}\right]^{1-\beta_s}, s = T \text{ or } N$$

where b_j^s is the output of input bundles in city j and sector s. In the tradable sector, the relative contributions of labor, intermediate goods from sector N and T to production is β_T, $(1-\beta_T)\eta_T$ and $(1-\beta_T)(1-\eta_T)$, respectively. Similarly, in the nontradable sector, the relative contributions of three inputs are β_N, $(1-\beta_N)\eta_N$ and $(1-\beta_N)(1-\eta_N)$, respectively.

Given the specification of production technology for input bundles, it is straightforward to obtain the price of an input bundle in city j and sector s as follows: [1] where P_j^N and P_j^T denotes the ideal price index in sector N and T in city j, respectively. w_j is wage rate in city j.

$$c_j^s = w_j^{\beta_s}\left[\left(P_j^N\right)^{\eta_s}\left(P_j^T\right)^{1-\eta_s}\right]^{1-\beta_s}, \quad s = T \text{ or } N$$

Intermediate goods market is featured in the fashion of monopolistic competition. Each intermediate goods is produced by a monopoly firm. Input bundle is the only input for production of intermediate goods. Firms are heterogeneous in term of their input bundle requirements for producing one unit of output. In other words, firms with higher productivities need less input bundles to produce one unit of output. Firms will realize their input bundle requirements (productivities) after they pay f_e^s units of input bundles to enter the sector s. They then randomly draw their input bundle requirement a from a distribution function $G(a)$. We let the distribution function be identical between the two sectors and follow a type-1 Pareto distribution as follows:

$$G(\frac{1}{a}) = 1 - \left(\frac{\mu}{y}\right)^{\theta}$$

[1] This is obtained by solving the following cost minimization problem:

$$\min w_j L_j + P_j^N N_j + P_j^T T_j$$
$$s.t. L_j^{\beta_s}\left[\left(N_j\right)^{\eta_s}\left(T_j\right)^{1-\eta_s}\right]^{1-\beta_s} = 1$$

Once the productivity is realized, firms also need to choose which markets to serve. In order for a firm from city j to serve market in city i, a fixed operating cost f_{ij} in term of input bundles of city j needs to be paid. [2] Moreover, standard ice-berg trade cost assumption also applies to tradable intermediate goods here. In order to deliver 1 unit of intermediate goods from city j to city i, firms need to ship $1+\tau_{ij}$ units at city j.

2.1 Firm's decision

We characterize firm's optimization problem in details in this subsection. Denote X_i^s to be the total expenditure on final goods s in city j. Standard CES utility function yields the following demand function of individual workers in city i for goods k of sector s:

$$q_i^s(k) = X_i^s \left(\frac{\varepsilon-1}{\varepsilon} P_i^s \frac{1}{\tau_{ij}} \frac{1}{c_j^s a(k)}\right)^{\varepsilon-1}$$

Firm with input bundle requirement a in sector s of city j will serve city i iff the profit can cover the fixed operation cost, that is:

$$\max\{\pi_{ij}^s(a) - f_{ij}^s c_j, 0\} \tag{1}$$

where $\pi_{ij}^s(a)$ is the maximum profit level obtained from solving the following profit maximization problem:

$$\begin{aligned} \max_{p_i^s(k)} p_i^s(k) q_i^s(k) &- a(k)\tau_{ij} q_i^s(k) c_j^s \\ s.t.\ q_i^s(k) &= X_i^s \left(\frac{\varepsilon-1}{\varepsilon} P_i^s \frac{1}{\tau_{ij}} \frac{1}{c_j^s a(k)}\right)^{\varepsilon-1} \end{aligned}$$

Standard monopolistic competition results apply. The optimal pricing and the resulting

[2] Firms in non-tradable sector only needs to decide whether to serve the local market or not. We can consider that f_{ij} is sufficiently large for firms in non-tradable sector.

sales revenue can be computed as follows:

$$\begin{aligned} p_i^s(k) &= \frac{\varepsilon}{\varepsilon-1}\tau_{ij}c_j^s a\left(k\right) \\ R_{ij}^s\left(k\right) &= \frac{X_i^s}{P_i^{s1-\varepsilon}}\left(\frac{\varepsilon}{\varepsilon-1}\tau_{ij}c_j^s a\left(k\right)\right)^{1-\varepsilon} \end{aligned}$$

Moreover, by setting inequality in equation (1) be equal, we can derive the cutoff a_{ij}^s below which firm in city j will serve city i:

$$a_{ij}^s = \frac{\varepsilon-1}{\varepsilon}\frac{P_i^s}{\tau_{ij}c_j^s}\left(\frac{X_i^s}{\varepsilon c_j^s f_{ij}^s}\right)^{\frac{1}{\varepsilon-1}}$$

We assume free entry holds in both tradable and non-tradable sector. Free entry condition in city j of sector s can be expressed as:

$$E\left[\sum_{i=1}^{J}\mathbf{1}\left(a\left(k\right)<a_{ij}^s\right)\left(\frac{X_i}{\varepsilon P_i^{1-\varepsilon}}\left(\frac{\varepsilon}{\varepsilon-1}\tau_{ij}c_j a\left(k\right)\right)^{1-\varepsilon}-c_j f_{ij}\right)\right]=f_e c_j$$

Given entry into sector s of city s, an operating firm is defined to be one that serves at least one market. This implies the following condition holds:

$$\pi_j(a)\equiv\sum_{i=1}^{J}\pi_{ij}^s(a)-f_{ij}^s c_j^s\geq 0$$

Denote the number of operating firms in each sector of city j as I_j^s. Therefore, the total number of varieties in city i and sector s can be written as:

$$\sum_{j=1}^{J} I_j^s prob\left(a\leq a_{ij}^s\right)$$

Finally, the price for final goods s in city i can be obtained as:

$$P_i^{s1-\varepsilon}=\sum_{j=1}^{J}\left(\frac{\varepsilon}{\varepsilon-1}\tau_{ij}c_j^s\right)^{1-\varepsilon}I_j^s\int_{-\infty}^{a_{ij}^s}a^{1-\varepsilon}dG\left(a\right)$$

2.2 Migration Decision

There is an initial population distribution over J cities. At the beginning of the period, each individual worker draws an idiosyncratic preference shock towards each city $\{\nu_i\}_{i=1}^{J}$, where ν_i is $i.i.d$ across locations and individuals. Therefore, the total utilities from staying in city i contains two components: a common term shared all by individuals living in the city, and an idiosyncratic term which vary among individuals.

Migration across cities will incur some costs in term of utilities. In reality, when people migrate to an unfamiliar city, they might suffer from being homesick or adjusting themselves to suit new working environment etc. Let λ_{ij} denote the costs of migrating from city j to i. Migration costs are identical to all individuals. Therefore, worker that initially lived in city j will migrate to city i iff living in city i leads him the highest utilities among all J cities, that is:

$$U_i + \nu_i - \lambda_{ij} \geq U_k + \nu_k - \lambda_{kj}, \forall k = 1, 2, ..., J$$

where U_i is the common utility level from living in city i, which essentially equals:

$$U_i = \left(\frac{\alpha w_i}{P_i^N}\right)^{\alpha} \left(\frac{(1-\alpha) w_i}{P_i^T}\right)^{(1-\alpha)} - c\left(N_i\right).$$

We assume ν_i follows a Gumbell distribution with CDF:

$$F(\nu_i) = \exp(-\exp(-\frac{\nu_i}{\kappa})).$$

It is straightforward to show that under these assumptions, the fraction of population migrate from city j to city i is:

$$m_{ij} = \frac{\exp(\frac{U_i - U_j - \lambda_{ij}}{\kappa})}{\sum_{k=1}^{J} \exp(\frac{U_k - U_j - \lambda_{kj}}{\kappa})}$$

2.3 Equilibrium

We summarize our equilibrium concept in this subsection.

Definition: Given a series of fixed costs, entry fee, trade costs, and migration costs $\{f_{ij}^s, f_e^s, \tau_{ij}, \lambda_{ij}\}$ in each city and sector, the equilibrium contains a series of prices $\{w_j, p_j^T(k), p_j^N(k)\}_{j=1}^J$, and a sequence of quantities $\{I_j^T, I_j^N, L_j, q_j^T(k), q_j^N(k)\}$ such that the following conditions hold:

(a) Individual workers maximize their utilities by choosing locations and consumption bundles of goods from both sectors.

(b) Each intermediate goods producer maximizes their profits by choosing price and quantity of output.

(c) Free entry condition holds in each city and sector.

(d) Goods market clearing:

$$\begin{aligned} X_i^N &= \alpha w_i L_i + (1-\beta_N)\,\eta_N X_i^N + (1-\beta_T)\,\eta_T X_i^T \\ X_i^T &= (1-\alpha)\,w_i L_i + (1-\beta_N)\,(1-\eta_N)\,X_i^N + (1-\beta_T)\,(1-\eta_T)\,X_i^T \end{aligned}$$

(e) Labor market clearing:

$$\sum_{j=1}^{J} L_j = \bar{L}$$

3 Calibration and Estimation

3.1 Estimation of the Geographic Trade Cost

We follow the approach in Allen and Arkolakis [2014] to estimate the matrix of geographic trade costs — denoted as $\{T(i,j)\}$ — across cities. Our estimation takes three steps: We first propose a discrete choice framework to evaluate the relative cost of trade using different transportation modes. Second, we discuss our approach on measuring the shortest distance between a pair of any two cities using the fastest transportation modes. Third, we discuss our structural estimation strategy and present our final results on the trade cost matrix.

Suppose there are M transportation modes indexed by $m = 1, 2...M$. For any pair of origin city i and destination city j, there exists a mass one of identical traders who will

choose a particular transportation mode in order to minimize the iceberg trade costs incurred from shipping a unit of good from i to j using transportation mode m, denoted as $\tau_m(i,j)$. Specifically, we let $\tau_m(i,j)$ take the following form:

$$\tau_m(i,j) = \exp(t_m d_m(i,j) + f_m + \nu_{tm}) \tag{2}$$

where $d_m(i,j)$ is distance from city i to j using transportation mode m. t_m is the mode-specific variable cost, f_m is the mode-specific fixed cost, and ν_{tm} is trader-mode specific idiosyncratic cost. We assume ν_{tm} is $i.i.d$ across traders and transportation modes, and follows a Gumbel distribution $Pr(e^{\nu} \leq x) = e^{-x^{-\theta_m}}$. The specifications above allow us to explicitly obtain the fraction of trade shipped from city i to j using transportation mode m as follows:

$$\pi_m(i,j) = \frac{\exp(-a_m d_m(i,j) - b_m)}{\sum_k (\exp(-a_k d_k(i,j) - b_k))},$$

where $a_m = \theta_m t_m$ and $b_m = \theta_m f_m$. We next proceed to estimate the mode-specific distance matrix $d_m(i,j)$. We convert each transportation mode network into a raster image covering mainland China using the 2005 China Map from Sino Map Press. Each raster image has resolution 4431-by-4371, so that each pixel roughly corresponds to a $1.3km$ by $1.3km$ square. We then assign a cost value to every pixel on the map to indicate the relative difficulty to travel through the area using a specific transportation mode. For example, to construct the normalized road network cost raster, we assign pixels with no road access to be 10, all pixels with highways to be 2.5, all pixels with national level road to be 3.75, and all pixels with provincial and other road access to be 6.0. All the costs are chosen to roughly reflect differences in relative travel speeds. Similarly, we normalize those pixels with navigable waterways, including open seas, a cost of 1, and all other pixels a cost of 10. To construct the normalized railroad cost raster, we assign all pixels with rail road access to be 1 and otherwise to be 10. We then identify the central location of each of the 279 cities on the raster maps, and apply the Fast Marching Method (FMM) algorithm between all pairs of cities i and j to get a normalized distance between them for each transportation mode, $d_m(i,j)$.

Given the mode-specific distance matrix, we next estimate the mode-specific parameters $\{a_m, b_m\}$ in equation 3.1. From *China City Statistics Yearbook 2005*, we are able to observe

the total trade volume of each city using transportation mode m. For instance, total trade volume in city i using rail includes the trade volume shipped from city i to all other cities by rail and the trade volume that delivered to city i from all other cities by rail. Formally, using the notation from our discrete choice framework the total trade volume of city i by transportation mode m ($V_m(i)$) equals to:

$$V_m(i) = \sum_{j=1}^{J} \exp(-a_m d_m(i,j) - b_m) + \sum_{j=1}^{J} \exp(-a_m d_m(j,i) - b_m).$$

The share of total trade volume using transportation mode m in city i, $s_m(i)$, can thus be expressed as:

$$s_m(i) = \frac{V_m(i)}{\sum_{k=1}^{M} V_k(i)}$$

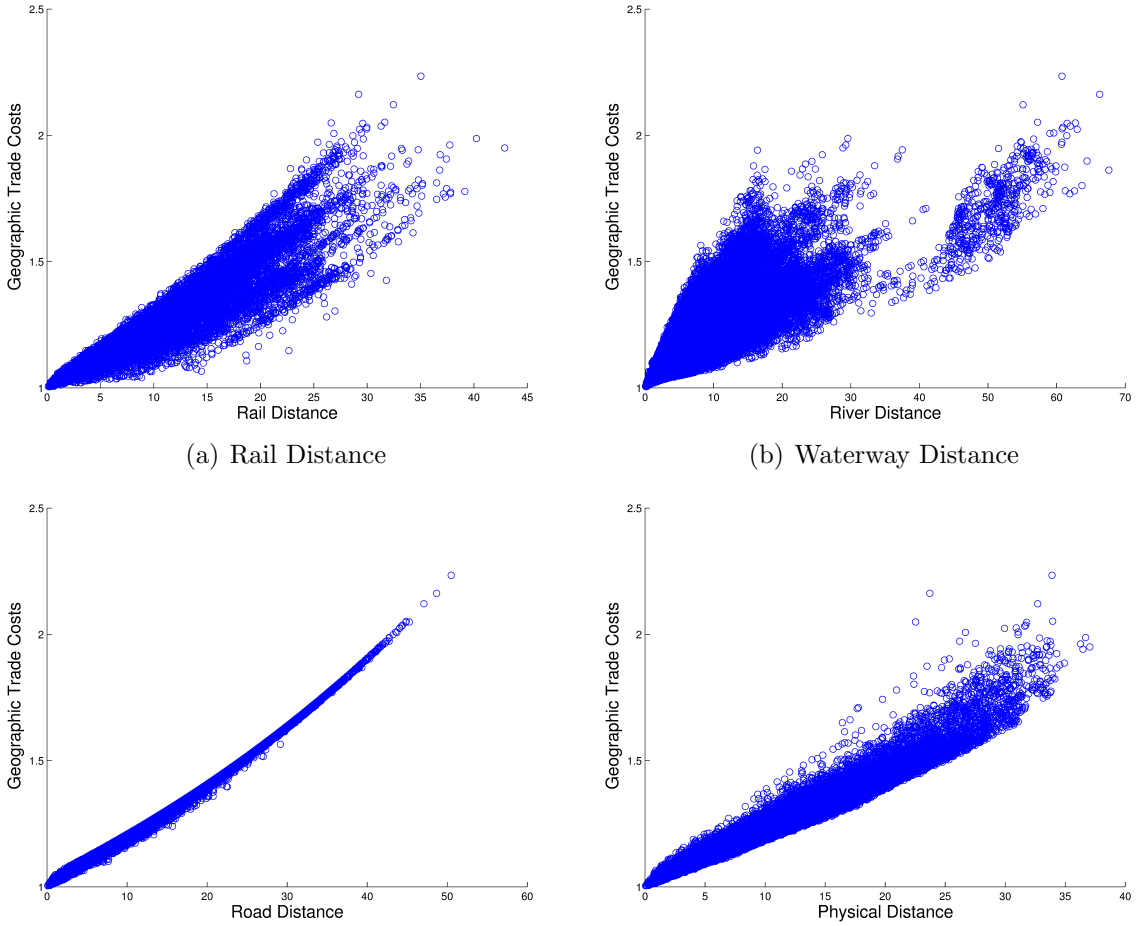
We estimate the sequence of $\{a_m, b_m\}$ using a non-linear least square routine to minimize the distance between the simulated $\{s_m(i)\}_{i=1}^{J}$ and the data counterpart. For the value of θ_m, we follow the estimations in Allen and Arkolakis [2014] and set it to be 17.65. Given $\{a_m, b_m\}$ and θ_m, we compute the mode-specific $\tau_m(i,j)$ using equation 2. In Figure 2 we present the transportation mode-specific iceberg trade cost between any two cities against the distance between the two cities measured using the specific transportation mode. Finally, the discrete choice framework implies that the average iceberg cost from city j to i can be obtained as follows:

$$T(i,j) = \frac{1}{\theta_m}\Gamma\left(\frac{1}{\theta_m}\right)\left(\sum_{m} \exp(-a_m d_m(i,j) - b_m)\right)^{-\frac{1}{\theta_m}},$$

where $\Gamma(\cdot)$ is the standard Gamma function.

We plot the estimated geographic costs matrix, $T(i,j)$, against different measures of distance in Figure 2. Unsurprisingly, the trade costs increase with distance regardless of the transportation mode. Out of the three modes of transportation, the estimated T matrix mostly depends on the distance through the road network. This is because all the cities in our sample have access to the national road system, and the vast majority of intra-China trade goes through the road network as well. On the contrary, iceberg costs start to vary

significantly between city pairs with similar rail or waterway distance. Traveling by river or coastal sea have the largest variation of iceberg cost, mainly because a large proportion of Chinese cities do not have easy access to any waterway.



(a) Rail Distance

(b) Waterway Distance

(c) Road Distance

(d) Physical Distance

Figure 2: Geographic Trade Costs by Transportation Mode

Note: The four panels above plot the estimated iceberg trade costs matrix, T, against the mode specific measures of distance obtained by FMM. The last panel plots the T matrix against physical distance between two cities, and the physical distances are normalized such that the distance between Beijing and Tianjin (110.9 KM) is 1.

We plot the T matrix against the physical distance between two cities in the last panel of Figure 2. The physical distance is measured by the Euclidean distance. We normalize the distance between Beijing and Tianjin, which is around 110.9 km, to be 1, and report the normalized physical distance in the figure. The iceberg trade costs increase with physical distance, and the variation in iceberg costs increases with the physical distances as well.

This is because cities trading with distant partners might diversify into different modes of transportation depending on the location of the partner, while they tend to exclusively rely on road transportation when trading with nearby neighbors.

3.2 Calibration

We calibrate the model into the Chinese economy. As of 2015, there were 334 prefectural level divisions and 2,852 county-level divisions. In this paper, we focus on a selection of 279 prefectural level cities due to data restrictions: our sample contains all the cities that are included in both the *Chinese City Statistical Yearbooks*, and the 2005 one percent population census. We illustrate cities in our sample in Figure 3. The vast majority of cities in China proper are included in our study. The missing cities are mainly those in Tibet, Xinjiang, Inner Mongolia, and various autonomous cities dominated by ethnic minorities in southwest China.

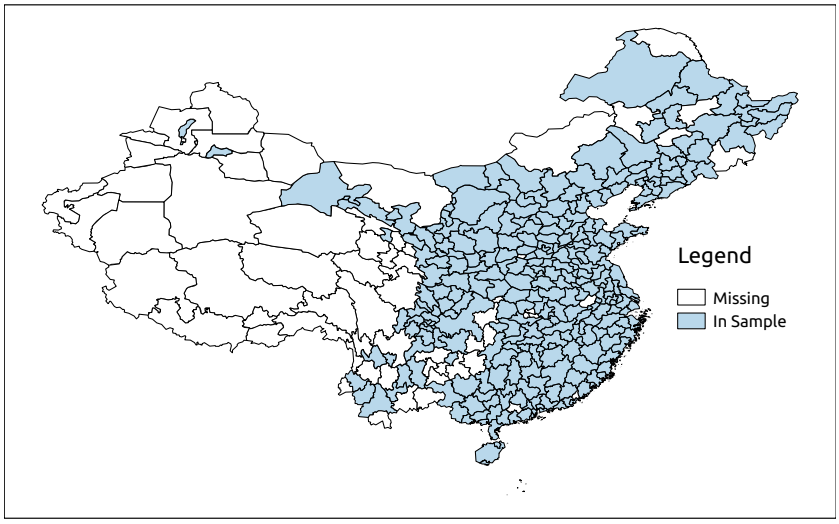


Figure 3: Prefectural-level Chinese Cities

Note: This graph plots the 279 prefecture level cities included in our sample. All the cities that are included both in the Chinese Statistical Year Books and the 2005 1 percent population census are in our sample.

Our parameter space contains the following structural parameters: $\{\epsilon, \theta, \mu, \beta_N, \beta_T, \eta_N, \eta_T, \alpha, \kappa, f_e\}$ and three series of origin-destination specific matrices $\{f_{ij}, \lambda_{ij}, \tau_{ij}\}$.

ϵ is the elasticity of substitution among all intermediate goods in the final goods production. This parameter generally ranges from 3 to 10 in the literature, and we pick the

middle value of 6. θ is the tail index of firm's productivity distribution. In our model the firms' employment follows a power law distribution with a tail index of $\theta/(\epsilon-1)$. We follow Di Giovanni and Levchenko [2012] by setting θ to be 5.3 so that the tail equals to 1.06, the value documented in Axtell [2001]. The values of β_N and β_T reflect the share of labor in total output, and we calibrate them using China 2002 input-output table. We use the basic flow table of 42 industries, and compute $\beta_N = 0.47$ and $\beta_T = 0.33$ as the ratio between total wage bills and total output in non-tradable and tradable sectors respectively. η_N and η_T are the share of non-traded intermediate goods in non-traded and traded sectors, and we also calibrate them using China 2002 input-output table. Data suggest that $\eta_N = 0.42$ and $\eta_T = 0.22$. Similar to what Di Giovanni and Levchenko [2012] documented using the U.S. data, intermediate goods from the non-tradable sectors play a larger role in the production of other non-tradable goods in the Chinese data as well. Different from the U.S. data, non-tradable goods are overall less important in the production of both sectors, probably because many services industries, such as finance and consulting, are relatively less developed in China. α governs expenditure share on non-tradable goods. We set it to be 0.61, the share of total consumption that goes into non-tradable goods, computed from the final use table in the input-output table of the same year.

The above 7 parameters are calibrated without solving the model. The calibration targets of the other parameters depend on the equilibrium outcome of the model, and thus calls for joint calibration. For the fixed operating costs matrix f_{ij}, we first turn to the Chinese 1 percent mini census in 2005, and approximate $1/f_{ii}$ by using the fraction of entrepreneurs in each city among all working population. Following Di Giovanni and Levchenko [2012] we set the off-diagonal elements, f_{ij}, as the sum of the two diagonal elements f_{ii} and f_{jj}. At this stage f_{ij} matrix is not yet in the unit of local labor, and to convert the f_{ij} matrix into the correct unit, we again follow Di Giovanni and Levchenko [2012] by scaling the entire matrix with a factor ζ. We set ζ to ensure interior solutions in all the counter-factual simulations.[3] We assume that the fixed cost of entry, f_e, is the same across different cities. f_e is the cost paid to reveal one's ability as an entrepreneur, which is unlikely to be affected

[3]Interior solution here means $a_{ij} <= 1/\mu$, where $1/\mu$ is the theoretical upper bound of the unit cost distribution. We calibrate ζ such that the number of entering firms is about twice the size of the number of operating firms in the benchmark model to guarantee that not all firms that enter choose to operate.

by the differences in infrastructures and institutions across Chinese cities. We calibrate this parameter to match the number of firms in Beijing in 2005, which is around 27 thousands.

The geographic iceberg trade cost matrix, T, describes the relative difficulties of transportation between different city pairs. We still need to pin down the overall scale of the T matrix to obtain a meaningful iceberg cost matrix, which we denote as τ. We again multiply the off-diagonal elements of the T matrix by $\bar{\tau}$, and calibrate this multiplier to match the overall volume of inter-city trade in China. We estimate the overall weight of internal trade with the Investment Climate Survey in China from World Bank [2005]. This survey covers 12,500 firms in all 31 provinces of China, and it asks the firms to report the percentage of their sales by regions: within the city, within the province, within China, and overseas. We find that 62.5 percent of total sales of the firms surveyed went into cities other than their home city, and thus calibrate $\bar{\tau}$ to reach the same trade/GDP ratio in our model.

The last group of parameters governs the congestion and migration costs. We discipline these parameters with the bilateral migration flows between 2000 and 2005. We first construct the bilateral migration matrix between any two cities using the 1 percent mini census in 2005 as follows:

$$M_{2000,2005} = \begin{bmatrix} \ell_{11} & \ell_{12} & \cdots & \ell_{1J} \\ \ell_{21} & \ell_{22} & \cdots & \ell_{2J} \\ \vdots & \vdots & \vdots & \vdots \\ \ell_{J1} & \cdots & \cdots & \ell_{JJ} \end{bmatrix}, \tag{3}$$

where ℓ_{ij} indicates the population flow from city j to city i between 2000 and 2005. Note that summation across the columns of the matrix generates the population distribution across cities in 2005, while summing over the rows of the matrix produces the population distribution in 2000:

$$L_{2005} = \begin{bmatrix} \sum_{j=1}^{J} \ell_{1j} \\ \sum_{j=1}^{J} \ell_{2j} \\ \vdots \\ \sum_{j=1}^{J} \ell_{Jj} \end{bmatrix} \quad L_{2000} = \begin{bmatrix} \sum_{j=1}^{J} \ell_{j1} \\ \sum_{j=1}^{J} \ell_{j2} \\ \vdots \\ \sum_{j=1}^{J} \ell_{jJ} \end{bmatrix}.$$

We use L_{2000} as the initial population distribution in our model, and calibrate the rest of the parameters so that the equilibrium population distribution and the bilateral population flows match L_{2005} and $M_{2000,2005}$ matrix respectively.

The migration cost matrix λ is city-pair specific. We model this matrix as proportional to the geographic trade cost matrix $\lambda = \bar{\lambda} \cdot T$: everything else being equal, it is generally easier to migrate to nearby cities, or along the major traffic networks. Similar to $\bar{\tau}$, we use $\bar{\lambda}$ to pin down the overall magnitude of inter-city migration. In the data 87 percent of the population stayed in the same city in 2005 as in 2000, and we match the same target in our model. Individuals living in different cities have very different propensities to emigrate. For example, less than 0.01 percent of the individuals living in Beijing in 2000 migrated to other cities in 2005, but emigration rate for some smaller cities can be as high as 49 percent. κ governs the dispersion of idiosyncratic migration cost, and we use it to match the standard deviations of the emigration rates in our model.

The last two parameters govern the congestion dis-utility. ρ controls the weight of congestion in the utility function, and ϕ controls the elasticity between population and congestion. Together they strongly influence the equilibrium size, or inward migration of the large cities in our model. We use ρ to match the overall inflow rate of Beijing (31 percent), which we index as city 1 in our model:

$$\text{Inflow Rate}_1 = \frac{\sum_{j=2}^{J} \ell_{1j}}{L_{1,2005}}.$$

Another salient feature of data is, people usually migrate from small to large cities. In the data the correlation between the net inflow rate and the logarithm of population of a city is around 0.4 and significantly different from zero. We use our last degree of freedom, ρ, to capture the general direction of migration flow, and match the corresponding correlation in our model.

We summarize all the parameter value and their corresponding targets in Table 1.

Para.	Targets	Para. Value
β_N	labor share in non-tradable sectors	0.47
β_T	labor share in tradable sectors	0.33
η_N	non-tradable share in non-tradable sectors	0.42
η_T	non-tradable share in tradable sectors	0.22
α	expenditure share on non-tradable goods	0.61
θ	Pareto index in emp. distribution	5.3
ϵ	elasticity of substitution	6
ϕ	corr(net inflow,population)	1.069
ρ	net inflow rate, Beijing	0.099
f_e	number of firms, Beijing	1.98
$\bar{\lambda}$	aggregate migration rate	0.008
κ	std of non-migration rates	0.0004
$\bar{\tau}$	internal trade/GDP ratio	1.543
ζ	entrants/operating firm ratio	0.211

Table 1: Benchmark Parameterizations

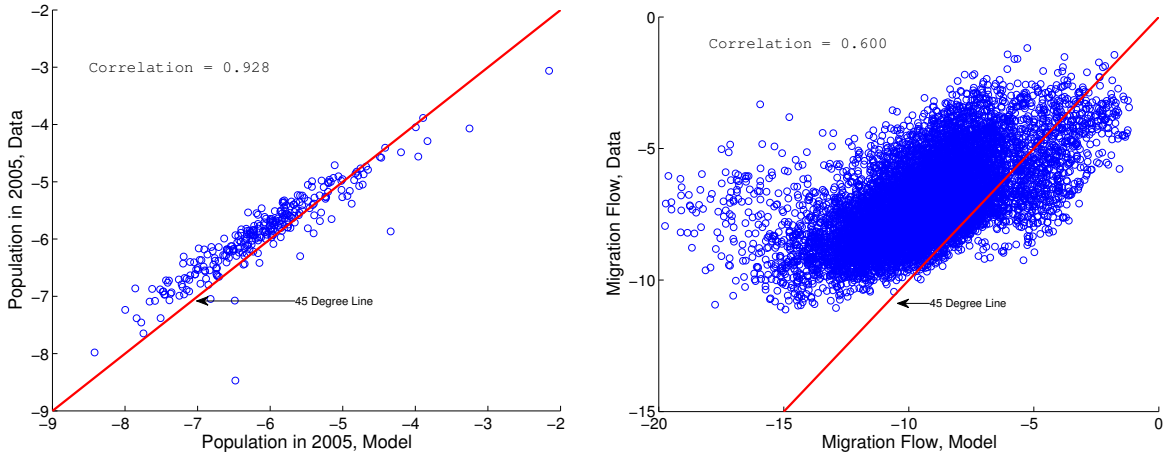
Note: The calibration targets for β_s, η_s and α come from the 2002 Chinese input-output table for 42 industries. The target for θ comes from Axtell [2001], the values for ϵ and ζ comes from Di Giovanni and Levchenko [2012]. The targets for f_e comes from the Chinese Manufacturing Firm Survey. The targets for $\phi, \rho, \bar{\lambda}, \bar{\tau}$ and κ come from the 2005 mini census.

3.3 Model Fit

We evaluate the fitness of our calibration strategy in two dimensions. First we show that by targeting a few moments of the migration matrix, our model is able to capture the population distribution and the bilateral migration flows fairly well. In our quantification of the model, the population distribution of year 2000 was used as the initial condition, and we discipline the model by targeting the migration matrix outlined in Equation 3. We plot the resulting population distribution and the bilateral migration in the model against their counter-parts in the data in Figure 4.

In the left panel, we plot population distribution of 2005 predicted by the model against its data counterpart. They are consistently lined up along the 45 degree line with a correlation coefficient of 0.928. In the right panel, we scatter plot the bilateral migration flow between all city-pairs with positive flows in the data. Our calibration strategy performs reasonably well: the correlation between model and data is 0.6. The magnitude of bilateral migration flows are mostly influenced by the specification of the λ matrix, which we assume

to be proportional to the geographical trade costs. The model fit validates our assumption: when individuals choose the migration destinations, nearby cities, or the cities located along main traffic networks are easier to reach to, and thus serves as better targets. The model tends to slightly over-predict when migration flow in the data is relatively small, and under-predict when the data value is relatively large. Given that we only target four moment conditions for the migration matrix, we view these discrepancies as affordable prices for our parsimonious quantification strategy.



(a) 2005 Population: Model v.s. Data (b) 2000-05 Migration Flow: Model v.s. Data

Figure 4: Model Fit: population distribution

Note: the graphs above plot the population distribution and the bilateral migration flows implied by the model against their counter-parts in the data. In both graphs the total population of China is normalized to be 1, and we plot the logarithms of the population and migration flows. The data source for both graphs is the 2005 mini census.

4 Quantitative Results

In this section we perform two counterfactual exercises. We first evaluate the impacts of migration on the equilibrium outcome. We simulate a counter-factual situation where individuals are not allowed to move across cities, by setting the migration cost multiplier λ to be sufficiently large. We compare the results to our benchmark calibration to study the impacts of migration.

We start our analysis with the aggregate impacts of migration. Our results show that over the span of five years cross-city migration increases the aggregate real income at the national level by 22.2 percent. This is a surprisingly large number, considering that the aggregate productivity is kept constant between the counter-factual and the benchmark economy. In comparison, over the same period, the real GDP of China only increased by around 54 percent.[4] This implies that around 41 percent of the economic growth can be explained by the re-allocation of population. We further decompose the gains in real income by examining gains obtained by two subgroups of individuals separately: migrants and the the stayers — those stayed in the same city in both year 2000 and 2005. Local labor market and product market at the local and national level jointly affect individuals' real income. Inflows of migrations tend to dampen the nominal wage in the destination cities; however, larger population also attracts more firms to enter, offering more employment opportunities and more varieties of products to choose from. At the national level, inflows into nearby cities can also have positive spillovers to the stayers, in the form of lower prices and more varieties of the tradable goods. All these impacts can also benefit the migrants. Moreover, migrants also benefit by moving from a low income to a high income city.

Formally we decompose the gains in real income as follows. The total gain in real income can be written as:

$$\Delta Y = L_{2005} \cdot \left(\frac{w_{2005}}{p_{2005}}\right) - L_{2000} \cdot \left(\frac{w_{2000}}{p_{2000}}\right),$$

where L, w and p are all J-by-1 vectors. The migration flows between the two years can be summarized by the following matrix: Then, ΔY can be decomposed as:

$$\Delta Y = \sum_{i=1}^{J} \ell_{ii} \cdot \left[\frac{w_{i,2005}}{p_{i,2005}} - \frac{w_{i,2000}}{p_{i,2000}}\right] + \sum_{i=1}^{J} \sum_{j \neq i} \ell_{ij} \cdot \left[\frac{w_{i,2005}}{p_{i,2005}} - \frac{w_{j,2000}}{p_{j,2000}}\right].$$

The first part of the above decomposition is the change in real wage for stayers, and the second part is for the migrants. Our quantification results suggest around 35 percent of the gain in real income can be attributed to the stayers, while the rest 65 percent are collected

[4]Data source: Penn World Table 8.1.

by the migrants. This implies that the majority of the gain of migration, or equivalently $41 \times 0.65 \approx 26.7$ percent of the change in total real GDP in the data, comes from reallocating workers and firms from low income to high income cities.

In the following, we move to discuss the welfare gains from counterfactual to the benchmark economy. Despite the surge in real wage, the total welfare in China only increased by around 5.55 percent between 2000 and 2005, due to higher congestion dis-utilities. Naturally we expect the burden of higher congestion dis-utilities to be born by those living and migrating to the large cities. Similar to the decomposition exercise that we performed for the case of real income, we decompose the change in total welfare in the following:

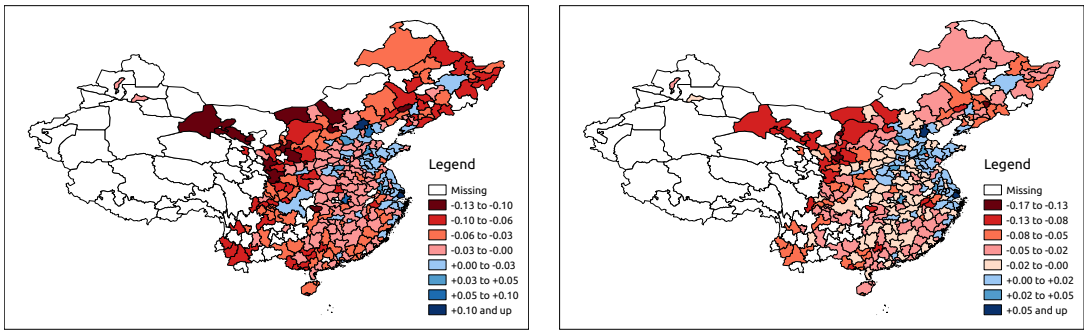
$$\Delta U = L_{2005} \cdot u_{2005} - L_{2000} \cdot u_{2000} \tag{4}$$

$$= \sum_{i=1}^{J} \ell_{ii} \cdot [u_{i,2005} - u_{i,2000}] + \sum_{i=1}^{J} \sum_{j \neq i} \ell_{ij} \cdot [u_{i,2005} - u_{j,2000}] . \tag{5}$$

Similar to the previous case, the first part summarizes the change to total utility for the stayers, and the second part for the migrants. We find that after taking the congestion dis-utilities into account, native populations actually slightly lose from 2000 to 2005, and the aggregate welfare gains from migration are purely distributed among the migrants. In the above equation, the utility change among the stayers constitute *-0.7 percent* of the total change, while the second term is responsible for *100.7* percent of the total change. As a result, this suggests that the benefits of higher real income for the native population are completely offset by higher congestion dis-utilities, such as higher housing prices, worsening pollution, and heavier traffic jams.

We measure trade openness using the percentage of trade volume in total GDP. The overall trade openness declined between 2000 and 2005 in our model from 71.85 percent to 62.50 percent. This seemingly counter-intuitive result is due to the substitutability between the movement of goods and population in our model. As more individuals migrate into larger cities in 2005, the demand for tradable goods in smaller cities decrease. In other words, the consumers of tradable goods choose to live closer to the site of production, and this depress the need for trade and leads to a decline in trade share in GDP.

City-level Impacts The aggregate gains in real wage are not uniformly distributed. Out of the 279 cities in our sample, only 49 cities experienced real wage growth, while all the other 230 cities suffered loss in real wage. The first panel in Figure 5 maps the change in real wage. The 49 "winners" of migration in term of real wage are usually the large and coastal cities in the eastern part of the country. Cities could benefit from migration through two channels. First, all the 31 cities that received net population inflows enjoy higher real wage. The mechanism here roots back to the idea of size effect found in the models following Krugman [1980] and Melitz [2003]. Larger population is able to support more firms in equilibrium, which in turn lowers the ideal price level of both tradable and non-tradable goods, and offers more varieties of products. The remaining 18 cities that enjoyed higher real wage all indeed experienced emigration. The reason that they are still better off in 2005 solely relies on their location: these cities all happen to be close to mega-cities like Beijing or Shanghai, or located along major traffic arteries, such as the Grand Canal or the Beijing-Shanghai railways. We highlight these cities in Figure 8. Higher real wage in these cities are the direct results of inter-city trade. The booming mega cities are able to produce more varieties of tradable goods at lower prices, and the benefits of the productivity boom spill over to other cities along the traffic networks. All the other cities lose in terms of real income, because they lose population to the large cities, yet at the same time, are not able to reap the benefit of productivity spillovers due to their locations.



(a) Real Wage (b) Welfare

Figure 5: Real Wage and Welfare

Note: The graphs above plot the change in real income and welfare between 2000 and 2005 due to inter-city migration implied by the model. The difference between real income and welfare is the congestion dis-utility. For more details, refer to section 4.

Similar to the case at the national level, not all the gains in real income can be translated into higher welfare. Megacities need to pay the price of immigration in terms of higher congestion dis-utility, leaving the overall impacts on welfare ambiguous. The most striking case here is Beijing. As the largest city in our sample, the real wage increased by as much as 64.2 percent in 5 years time purely due to immigration. By the end of our simulation, around 31 percent of the people living in Beijing came from other cities. However, the explosive population growth imposes a congestion dis-utility even higher than the gain in real wage, leaving the native Beijing residents slightly worse off by around 0.5 percent. In addition to Beijing, Chengdu and Chongqing also see their gain in real wage completely wiped off by higher congestion dis-utility. Nevertheless, the vast majority of cities that received net population inflow still enjoyed higher welfare. Moreover, the 18 "lucky" cities we mentioned before with emigration and higher real income are, unsurprisingly, gaining welfare.

To sum up, 55 cities in our sample end up with higher welfare, and the other 224 cities lose in welfare. The first panel in Figure 6 plots the top 10 winners in gaining welfare. All the top 10 winners are migration inflow-cities, and the top 1 winner is Tianjin, with a net welfare gain of 5.6 percent, followed by Shanghai, Wuhan, Zhengzhou and etc. These cities benefit substantially from migration partly due to their locations. Tianjin, along with Shijiazhuang and Baoding, are only a few hundred kilometers away from Beijing, and thus are the most direct recipient of the productivity spill overs. Wuhan and Zhengzhou are arguably among the most strategically placed cities in China. Wuhan sits at the cross-road of Yangtze river that connects the western inland provinces with the eastern coast, and the Beijing-Guangzhou railway, which connects the northern and the southern economic hubs of China. Similarly, Zhengzhou sits at the center of several major railways, and it hosts the largest railway station by traffic volume in the country. In our estimation of the T matrix, Zhengzhou is also the most centrally-located city in China, with the lowest average geographic trade costs, T_{ij}, to the other cities.

The vast majority of the cities are negatively affected in terms of welfare. The second panel of Figure 6 plots the top 10 losers in terms of welfare. The top 1 "loser" is Guyuan, followed by Jiayuguan and Shizuishan, all located in the remote western frontier of China proper. All the cities on the list share two common features: they lose population to large

coastal cities in the east, and yet their remote locations denied any easy access to the productivity spillovers from the east. The same two mechanism apply to all the losing cities in different magnitudes.

Lastly we highlight the changes on the firm's side to help better understand the linkage between migration and real income. The first panel in Figure 9 maps the change in number of operating firms. As expected, the vast majority of cities see dwindling number of firms, and only the handful inflow cities see otherwise. Again, the linkage between population and number of firms is at the core of our model mechanism. However, some smaller cities can still benefit from the concentration of economic activities in the large cities through inter-city trade, which can be seen from the map on real wage in Figure 5.

5 Conclusion

To be completed.

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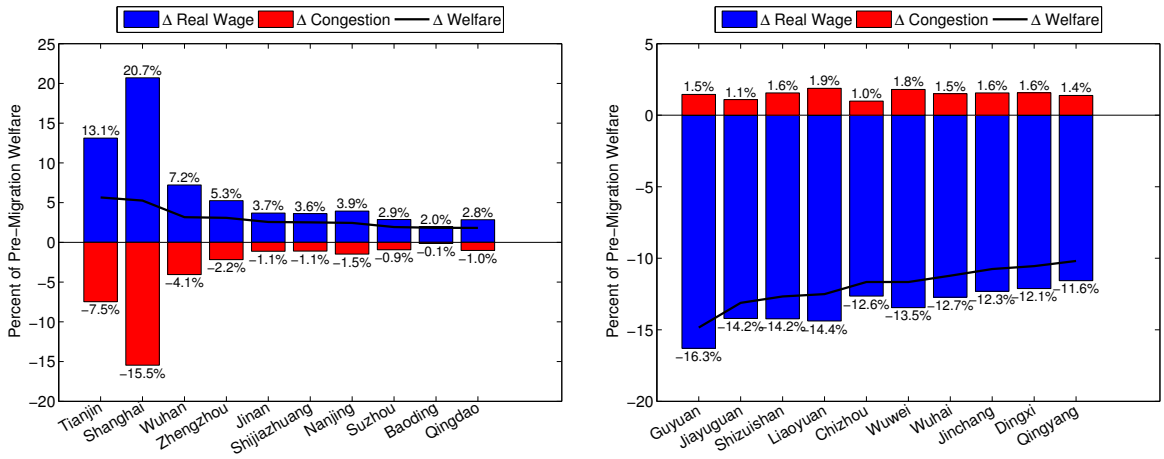
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A Tables and Figures

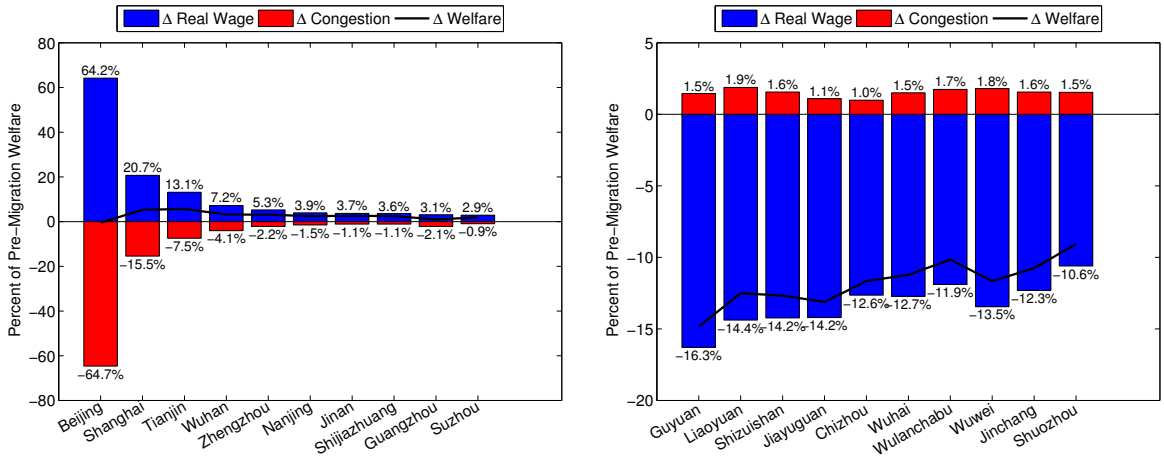


(a) Top 10 Winners

(b) Top 10 Losers

Figure 6: Winners and Losers from Migration

Note: The two panels above plot the change in real wage and congestion costs as a percentage of welfare before and after migration. The first panel plots the top 10 cities in terms of percentage change in welfare, and the second panel plots the bottom 10 cities according to the same measure.

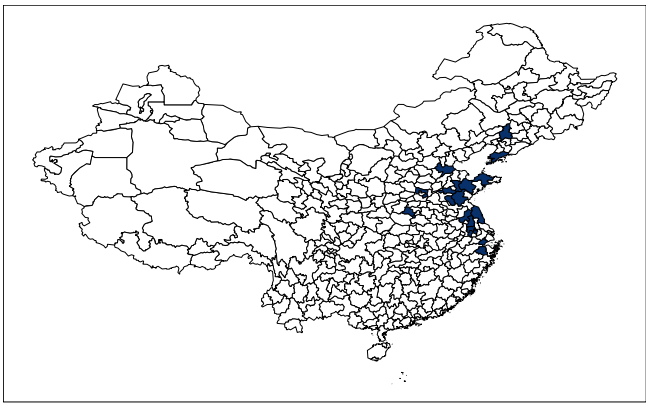


(a) Top 10 Inflow

(b) Top 10 Outflow

Figure 7: Welfare from Migration, by Migration Flow

Note: The two panels above plot the change in real wage and congestion costs as a percentage of welfare before and after migration. The first panel plots the top 10 cities in terms of population inflow rate, and the second panel plots the bottom 10 cities according to the same measure.



City	Remoteness
Cangzhou	1.1959
Shenyang	1.2795
Dalian	1.2696
Changzhou	1.1977
HuaiAn	1.1862
Yancheng	1.1975
Yangzhou	1.1933
Zhenjiang	1.1902
Jiaxing	1.2061
Shaoxing	1.2038
Zibo	1.1960
Zaozhuang	1.1795
Yantai	1.2274
Weifang	1.2067
TaiAn	1.1844
Linyi	1.1911
Pingdingshan	1.1729
Anyang	1.1800
National Average	1.2460

Figure 8: Cities with Net Outflow and Higher Real Wage

Note: The 18 cities in the map here are those who see net population outflow, and at the same time, enjoy higher real wages between 2000 and 2005. The table lists the average remoteness of these cities, defined as the average iceberg trade costs to all the other cities.

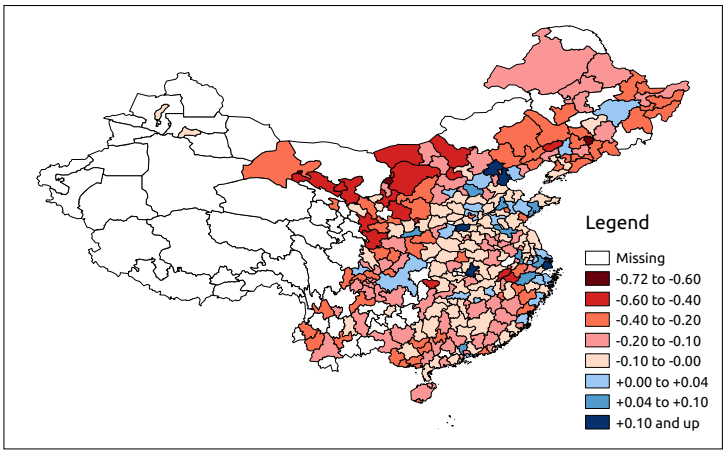


Figure 9: Number of Firms

Note: This map plots the changes in the number of operating firms, both in tradable and non-tradable sectors between 2000 and 2005, as implied by the model.

B Solving the Model

In each city, we need to solve $\left\{w_j, I_j^N, I_j^T, P_j^T, P_j^N\right\}$. When we assume $\frac{1}{a}$ follows a type-1 Pareto distribution: $\Pr\left(\frac{1}{a} < y\right) = 1 - \left(\frac{b}{y}\right)^\theta$, then we can explicitly derive:

$$\begin{aligned} P_i^N &= \frac{1}{b_N}\left[\frac{\theta_N}{\theta_N - (\varepsilon_N - 1)}\right]^{\frac{-1}{\theta_N}} \frac{\varepsilon_N}{\varepsilon_N - 1}\left(\frac{X_i^N}{\varepsilon_N}\right)^{-\frac{\theta_N - (\varepsilon_N - 1)}{\theta_N(\varepsilon_N - 1)}} \\ &\quad \left(I_i^N\left(\frac{1}{c_i^N}\right)^{\theta_N}\left(\frac{1}{c_i^N f_{ii}^N}\right)^{\frac{\theta_N - (\varepsilon_N - 1)}{\varepsilon_N - 1}}\right)^{\frac{-1}{\theta_N}} \end{aligned} \tag{6}$$

$$\begin{aligned} P_i^T &= \frac{1}{b_T}\left[\frac{\theta_T}{\theta_T - (\varepsilon_T - 1)}\right]^{\frac{-1}{\theta_T}} \frac{\varepsilon_T}{\varepsilon_T - 1}\left(\frac{X_i^T}{\varepsilon_T}\right)^{-\frac{\theta_T - (\varepsilon_T - 1)}{\theta_T(\varepsilon_T - 1)}} \\ &\quad \left(\sum_{j=1}^{J} I_j^T\left(\frac{1}{\tau_{ij} c_j^T}\right)^{\theta_T}\left(\frac{1}{c_j^T f_{ij}^T}\right)^{\frac{\theta_T - (\varepsilon_T - 1)}{\varepsilon_T - 1}}\right)^{\frac{-1}{\theta_T}} \end{aligned} \tag{7}$$

Free entry condition in each city/sector gives:

$$\frac{X_j^N}{\varepsilon P_{jN}^{1-\varepsilon}}\left(\frac{\varepsilon}{\varepsilon - 1} c_j^N\right)^{1-\varepsilon} \frac{\theta b^\theta a_{jN}^{1+\theta-\varepsilon}}{1 + \theta - \varepsilon} = c_j^N f_e + b^\theta a_{jN}^\theta c_j^N f_{jj} \tag{8}$$

$$\sum_{i=1}^{J} \frac{X_i^T}{\varepsilon P_{iT}^{1-\varepsilon}}\left(\frac{\varepsilon}{\varepsilon - 1}\tau_{ij} c_j^T\right)^{1-\varepsilon} \frac{\theta b^\theta a_{ij}^{1+\theta-\varepsilon}}{1 + \theta - \varepsilon} = c_j^T f_e + \sum_{i=1}^{C} b^\theta a_{ij}^\theta c_j^T f_{ij} \tag{9}$$

where a_{jN} and a_{ij} are from zero profit conditions:

$$\begin{aligned} a_{jN} &= \frac{\varepsilon - 1}{\varepsilon}\frac{P_{jN}}{c_j^N}\left(\frac{X_j^N}{\varepsilon c_j^N f_{jj}}\right)^{\frac{1}{\varepsilon - 1}} \\ a_{ij} &= \frac{\varepsilon - 1}{\varepsilon}\frac{P_{iT}}{\tau_{ij} c_j^T}\left(\frac{X_i^T}{\varepsilon c_j^T f_{ij}}\right)^{\frac{1}{\varepsilon - 1}} \end{aligned}$$

where

$$\begin{aligned} X_i^N &= \alpha w_i L_i + (1 - \beta_N)\,\eta_N X_i^N + (1 - \beta_T)\,\eta_T X_i^T \\ X_i^T &= (1 - \alpha)\,w_i L_i + (1 - \beta_N)\,(1 - \eta_N)\,X_i^N + (1 - \beta_T)\,(1 - \eta_T)\,X_i^T \end{aligned}$$

Finally, balance of trade condition requires $X_i^T = \sum_{j=1}^J X_{ji}^T$, so in each country i we have $w_i L_i$ equals to the following:

$$w_i L_i = \sum_{j=1}^{J} \frac{I_i^T \tau_{ji}^{-\theta_T} \left(f_{ji}^T\right)^{-\frac{\theta_T-(\varepsilon_T-1)}{\varepsilon_T-1}} \left(w_i^{\beta_T}\left[\left(P_i^N\right)^{\eta_s}\left(P_i^T\right)^{1-\eta_T}\right]^{1-\beta_T}\right)^{-\frac{\theta_T-(\varepsilon_T-1)}{\varepsilon_T-1}}}{\sum_{l=1}^J I_l^T \tau_{jl}^{-\theta_T} \left(f_{jl}^T\right)^{-\frac{\theta_T-(\varepsilon_T-1)}{\varepsilon_T-1}} \left(w_l^{\beta_T}\left[\left(P_l^N\right)^{\eta_s}\left(P_l^T\right)^{1-\eta_T}\right]^{1-\beta_T}\right)^{-\frac{\theta_T-(\varepsilon_T-1)}{\varepsilon_T-1}}} w_j L_j \quad (10)$$

Given the initial distribution of labour $\left\{\overline{L_i}\right\}$, the labour supply in country i is $L_i^S = \sum_{j=1}^{J} m_{ij}\overline{L_j}$

Then the total demands for labour in city i is

$$\begin{aligned} L_i^D &= I_i^N \frac{\beta^N C_i^N}{w_i} \frac{X_i^N}{\left(P_i^N\right)^{1-\varepsilon}} \left[\frac{\varepsilon}{\varepsilon-1}\tau_{ii} c_i^N\right]^{-\varepsilon} \frac{\theta b^\theta \left(a_{ii}^N\right)^{1+\theta-\varepsilon}}{1+\theta-\varepsilon} \\ &\quad + I_i^T \sum_{j=1}^{J} \frac{\beta^T C_i^T}{w_i} \frac{X_j^T}{\left(P_j^T\right)^{1-\varepsilon}} \left[\frac{\varepsilon}{\varepsilon-1}\tau_{ji} c_i^T\right]^{-\varepsilon} \frac{\theta b^\theta \left(a_{ji}^T\right)^{1+\theta-\varepsilon}}{1+\theta-\varepsilon} \end{aligned}$$

Labour market clearing gives:

$$\sum_{j=1}^{J} m_{ij}\overline{L_j} = I_i^N \frac{\beta^N C_i^N}{w_i} \frac{X_i^N}{\left(P_i^N\right)^{1-\varepsilon}} \left[\frac{\varepsilon}{\varepsilon-1}\tau_{ii} c_i^N\right]^{-\varepsilon} \frac{\theta b^\theta \left(a_{ii}^N\right)^{1+\theta-\varepsilon}}{1+\theta-\varepsilon}$$

$$+ I_i^T \sum_{j=1}^{J} \frac{\beta^T C_i^T}{w_i} \frac{X_j^T}{\left(P_j^T\right)^{1-\varepsilon}} \left[\frac{\varepsilon}{\varepsilon-1}\tau_{ji} c_i^T\right]^{-\varepsilon} \frac{\theta b^\theta \left(a_{ji}^T\right)^{1+\theta-\varepsilon}}{1+\theta-\varepsilon}, \forall i$$

In total, we have $5 * J + (J-1)$ equation to solve for $w_j, I_j^N, I_j^T, P_j^T, P_j^N, L_j$, where we normalize one city's wage rate to be 1.

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